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Binary Back Propagation Based Lift Association Mining For Heart Disease And Stroke Identification

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Abstract

Huge amount of healthcare data with voluminous amount of processing using traditional models calls for technological advancements to facilitate efficient management of those data. With effective decision making, voluminous data can be processed by applying data mining that discovers the hidden patterns and trends in relationships with disease patterns. Most of the existing Ventricular arrhythmias associated with acute stroke though focus on pattern prediction for continuous cardiac monitoring, neurological function on identifying risk factors for heart disease and stroke patterns are not focused. Early works on neural networks for 3D pattern prediction learnt spatio-temporal relationships for early stroke occurrence, but not for detection of heart disease and stroke. In this work, our goal is to design a framework for detecting heart disease and stroke in healthcare. Accordingly, we propose a framework called Binary Back Propagation based Lift Association (BBP-LA) framework to improve the heart disease and stroke identification at an early stage and also increase the accuracy rate. The Binary Back Propagation Neural Network extracts the input heart disease and stroke pattern and performs the back propagation twice. The extraction of disease patterns using binary (i.e., twice) back propagation increase the precision score on heart disease and stroke identification process. A Neural Network pruning algorithm is applied in BBP to reduce the time taken for identification of disease. The Neural Network pruning algorithm uses the activation of hidden unit in BBP-LA framework for heart disease and stroke instead of activation of the input value, minimizing the time taken to identify the disease pattern. The identified heart disease and stroke patterns are efficiently classified using Lift Association Data Mining Classification model. The framework BBP-LA shows that the Lift Association Data Mining Classification model in neural network is trained to achieve required accuracy rate. Experimental results demonstrate that the proposed detection of heart disease and stroke achieves efficient amount of precision, accuracy, heart disease and stroke identification rate with minimum processing time.

Keywords: Ventricular arrhythmias, Pattern prediction, Spatio-temporal relationships, Back propagation, Neural network, Lift Association.

Introduction

In the last few decades, several research works were focused on applying neural networks in the diagnosis of heart disease and stroke identification. Stroke and Ventricular Arrhythmias (SVA) [1] in relation to acute stroke concentrated heavily on predicting the pattern rates for the effectual monitoring of cardiac disorders. However, neurological function related to identification of risk factors for heart disease and stroke patterns were not focused. Another method for effective classification and prediction of stroke called, Spiking Neural Networks on Stroke (SNN-S) [2] was designed with the objective of improving the accuracy and time for prediction using Spatio Temporal Pattern Recognition (STPR). But, early detection of heart disease and stroke were not performed on neural networks using spatio-temporal relationships.

To analyze the early diagnosis of stroke, using plasma N-terminal, a method called, Prohormone of Brain Natriuretic Peptide (PBNP) [3] was presented. This method was proved to be efficient in terms of prediction accuracy. However, small number of patient's series was one of the main drawbacks. To solve this problem, multivariable logistic regression was applied in [4] to derive the relationship between stroke and arthritis. With the application of multivariable logistic regression, the model was proved to be efficient in terms of odds ratio with respect to stroke risk factors.

Epidemiologic transition refers to the increase in non communicable disease and decrease in nutrition and infectious disease. In [5], risk related to cardiovascular disease was analyzed based on the population, age and individual aspects. Cardiovascular diseases with respect to atherosclerotic were estimated based on Framingham Risk Score (FRS) [6]. However, clinical evidence of vascular disease remained unaddressed. Systematic review and meta-analysis [7] was introduced for vascular disease resulting in the early detection of disease with concurrent cardiac and carotid disease. Though early detection was made, prediction was not performed. In [8], predicting the risk related to Coronary Heart Disease (CHD) was introduced with the objective of improving the accuracy of atherosclerosis using Particle Swarm Optimization (PSO).

With the significant technological advancement in recent years have identified and measured the relationships between genes and stroke using Genome Wide Association Studies [9]. The method used to obtain better knowledge with respect to stroke and prevention from it. Another framework was introduced in [10] where physical activity had higher influential factor on ischemic stroke using neuro-protective mechanisms. However, classification with respect to cerebrovascular disease was not conducted.

In [11], data mining algorithms like Naïve Bayes, CART was introduced to identify the predictive performance of the classifiers with the aid of decision tree model. Though reliability was ensured, sources and risk factors related to heart disease remained unsolved. In [12], risk factors related to stroke disease were identified using atrial fibrillation.

Here, we propose a framework called Binary Back Propagation based Lift Association (BBP-LA) for heart disease and effective identification of stroke at an early stage. The contributions of the BBP-LA framework include the following:

- To improve precision score on heart disease and stroke identification process using Binary Back Propagation Neural Network
- To reduce the processing time to identify the heart and stroke disease using Neural Network Pruning algorithm by activation of hidden unit instead of activation of input value
- To increase the accuracy rate of classification with the help of Lift Association Data Mining Classification in addition to support and confidence value

The rest of the paper is organized as follows. Section 2 presents the review of literature presented by different researchers. Section 3 introduces the proposed framework called Binary Back Propagation based Lift Association. Section 4 includes the experimental setup and Section 5 discusses the results with aid of table values and graphical representation. Finally, Section 6 concludes with concluding remarks.

Related Works

Two main causes of death occurring worldwide are heart attack and stroke. According to the statistics provided by the World Health Organization, about 7.3 million deaths were caused due to the coronary heart disease whereas 6.2 million deaths were caused due to stroke [13]. Validated sampling frame was collected in [14] and the reasons behind the coronary heart disease and stroke were analyzed based on demographics. However, interviewers biased role was observed to be one of the main disadvantages.

In [15], risk factors related to cardiovascular diseases was analyzed based on the demographics using large datasets and comparison was made between ethnic groups. In [16], a protocol was developed to study and analyze the rate of cancer survivor patients. The reasons behind the disease were also measured using regression analysis to measure the differences between the mean arterial pressure and circumference of the weight.

Several factors are responsible for the stroke disease that includes age, mechanism, severity of the disease, location and their clinical findings. With these factors, medical practitioners are identifying and measuring the risk factors and constructed many preventive measures to control the disease. In [17], relationships between blood pressure and stroke were measured using the J-curve phenomenon. But, randomized trials remained an open issue to be solved. To address this issue, a randomized mechanism called meta-analysis was introduced in [18] with the motive of identifying the correlation between serum and cardiovascular disease.

Two main non-communicable forms of cardiovascular diseases involved are hypertension and heart disease. In [19], the effects and the preventive measures were analyzed using transition mechanisms in African woman. However, the method involved high cost and time taken to analyze also increased with the increase in the population. Remote monitoring of stroke disease was performed in [20] to provide a cost and time efficient system using accelerometer sensor system.

The above mentioned factors paved the way for analyzing and measuring the cause of disease and preventive measures were also taken. However, heart disease and stroke identification were not performed in a combined manner. In this work, we design a framework called, binary back propagation using lift association to identify heart disease and stroke at an early stage.

Binary Back Propagation Using Lift Association (BBP-LA) Framework

Computer Aided Data mining based decision support system plays a major role in the research for easy diagnosis of disease at an early stage. With the growing research work in heart disease and stroke identification, it has become apparent to categorize the research outcomes and provide an effective pattern matching to the readers. A framework called Binary Back Propagation based Lift Association for heart disease and stroke identification using Cleveland Heart Disease Dataset (CHDD) is presented. The framework BBP-LA uses two models. The first model Binary Back Propagation Neural Network with Neural Network pruning algorithm and Lift Association Data Mining Classification is used.

Design of Binary Back Propagation Neural Network

The framework BBP-LA presents a neural network based on Binary Back Propagation (BBP) that identifies the heart disease and stroke at an early stage. The objective of BBP is training hidden layer neural network with binary back-propagation for large dataset. Once the data (i.e., disease pattern) is obtained, then the next step is to train the neural network using Binary Back Propagation Neural Network. The extraction of disease patterns using binary (i.e., twice) back propagation increase the precision score on heart disease and stroke identification process.

The Binary Back Propagation Neural Network is trained with Heart and stroke Diseases dataset and Neural Network pruning algorithm is applied with momentum and variable learning rate. The input disease pattern (as in Figure 2) consists of 7 neurons and the four classes obtained are 0 – Normal affected person, 1 – Slightly affected person and 2 – Highly affected person and 3 – Very highly affected person. The output layer includes four neurons to represent these four disease classification patterns. By applying Binary Back Propagation, with different number of input disease patterns, twice, helps in increasing the precision score of extracted disease patterns.

The construction of Binary Back Propagation Neural Network is shown in Figure 1. The Neural Network on figure has four input nodes ‘$I_{o,o}, I_{o,1}, I_{o,2}$ and $I_{o,3}$‘in the input layer with two nodes in hidden layer ‘$I_{1,o}, I_{1,1}$’ and one output layer ‘$I_{2,o}$’. The input layer is connected to the output layer through weights ‘$Weight_4$’ ‘$Weight_5$’

and connected to hidden layers through '$Weight_0$', '$Weight_1$', '$Weight_2$', '$Weight_3$'respectively. The computation of weights is explained in 1.2.

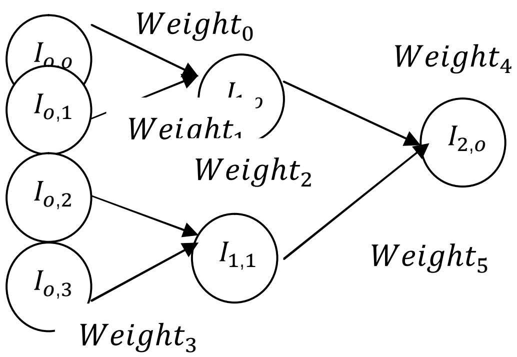

Figure 1: Construction of Binary Back Propagation Neural Network

Figure 1shows the construction of Binary Back Propagation Neural Network. The binary applied in Back Propagation Neural Network refers to two time classification of input nodes into one of two possible cases as either $O_{i,j} = 0$ or $O_{i,j} = 1$. Then, the Binary Back Propagation is formalized as

$$BBP = O_{i,j} = 0 \;\&\&\; O_{i,j} = 1 \tag{1}$$

$$O_{i,j} = 1 \mid \left(I_{i,j}\right) = Prob(O_{i,j}) \tag{2}$$

$$O_{i,j} = 0 \mid \left(I_{i,j}\right) = 1 - Prob(O_{i,j}) \tag{3}$$

From (1), (2) and (3), the Binary Back Propagation using the values of '0' and '1' is performed twice to produce higher precision score on the heart and stroke disease identification.

Neural Network pruning algorithm

Once the precision score is increased using Binary Back Propagation Neural Network, the time taken to identify the diseased pattern is to be reduced. In Neural Network, the relationship between hidden neuron and the error are highly related to the output to which it is said to be connected. This error rate has greater influential factor on predicting the deviation which when not properly designed increases the time taken to identify the heart and stroke disease and reduces the efficiency of pattern identification.

To provide solution to this problem, a Neural Network Pruning (NNP) algorithm is designed in such a way that instead of using the activation of input value, the BBP-LA framework uses activation of hidden unit for pattern identification (i.e., heart and stroke disease) that substantially reduce the number of hidden neurons. The NNP algorithm with activation of hidden unit is applied in BBP-LA that reduces the time taken for pattern identification of disease.

The NNP algorithm measures the synaptic weights of neural network to obtain the desired output for a set of input patterns (i.e., heart disease and stroke). As the neural network with binary back propagation identifies the optimized solution, the NNP uses it for initializing the weights for neural network. Thus, the proposed framework with BBP-LA is used for efficient identification of disease pattern. Figure 2 shows the construction of Neural Network Pruning.

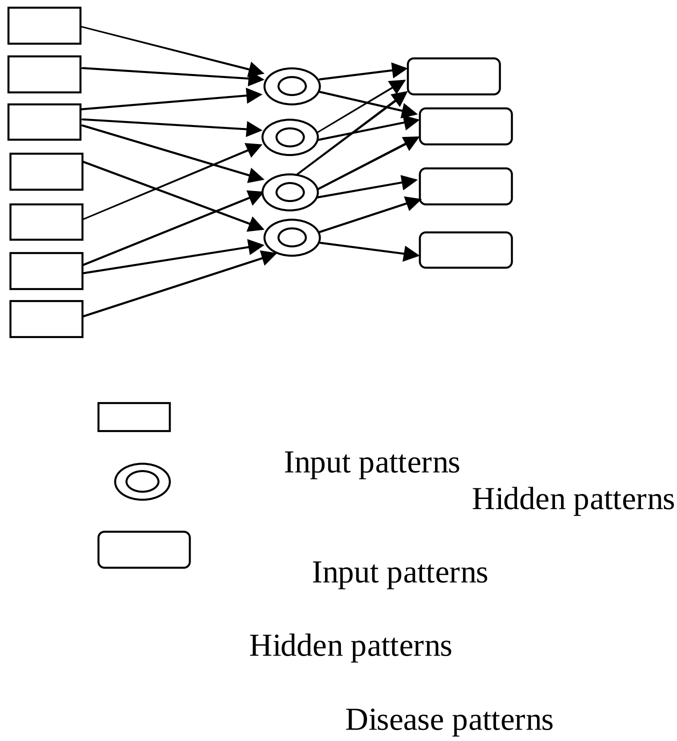

Figure 2: Construction of Neural Network Pruning

As shown in the figure, given with a set of input patterns, the objective of neural network pruning in BBP-LA framework is to obtain the disease patterns at relatively lesser amount of time. The figure shows seven different input patterns, with four hidden nodes. By applying the neural network pruning, least square function is used in BBP-LA framework to reduce the error rate.

Let us consider that there are seven different input patterns IP_i with four hidden patterns HP_ithat includes both heart disease and stroke in the form of(A_i, B_i). Then, the number of input patterns is measured using the final disease pattern DP_i and the number of hidden patterns HP_i that together produces the identified disease pattern.

The hidden patterns in BBP-LA framework using the neural network pruning algorithm is obtained using a synaptic weight α so that the least square function becomes minimal, reducing the time taken for trial and error. As a result the processing time for identification of disease pattern gets reduced. The least square function is formalized as given below

$$LSF = \sum_{i=1}^{n} [(A_i, B_i) * \alpha]^2 \tag{4}$$

From (4), the least square function is obtained as the product of different input patterns to the synaptic weight. According to the changes observed in the input patterns, the corresponding synaptic weight also changes resulting in different square function. The adjustments in synaptic weights are made according to deltas for measuring the stroke pattern and identify the heart disease and finally to reduce the error. The deltas (i.e., weights) for measuring the disease patterns is formalized as given below

$$\Delta = \sum_{i=1}^{n} {(DP_i - HP_i)}/{HP_i} \tag{5}$$

Input: Input patterns, Hidden layers
Output: Generated output patterns
Begin
Step 1: Repeat
Step 2: For each input disease pattern
Step 3: Measure the weights
Step 4: Measure the error
Step 5: Obtain the least square function
Step 6: Measure the output diseased patterns
Step 7: End for
Step 8: Until (error is small)
End

From (5), the weights are obtained
which is the difference between the desired diseased patterns and actual diseased patterns. Based on the weights obtained through Neural Network Pruning, the time taken to identify the disease pattern is minimized.

Algorithm 1 - Neural Network Pruning

The Neural Network Pruning algorithm is divided into four steps. For each disease pattern, the weights, error and least square function is obtained. Based on these three values, the output diseased patterns are obtained. The output diseased patterns obtained get changed according to the error rate. So the algorithm is repeated until the error rate is small. The application of Neural Network Pruning algorithm in BBP-LA framework that uses the activation of hidden unit, instead of the input unit reduces the time to identify diseased patterns.

Lift Association Data Mining Classification (increase accuracy)

Finally, the accuracy of diseased patterns is improved by applying Lift Association Data Mining Classification in BBP-LA framework. Association Data Mining Classification (ADMC) helps in increasing the accuracy of the diseased patterns obtained through neural network. However, the drawback concerned with Association Data Mining is the vast amount of rules generated that are highly irrelevant to healthcare.

The BBP-LA framework uses Lift Association Data Mining for efficient classification and to improve the accuracy rate and obtain the diseased pattern at an early stage. The conventional association rule mining uses two values namely, support and confidence, to measure the reliability and accuracy of association rules. The BBP-LA framework in addition to support and confidence value uses the lift value to validate association rules and to improve the accuracy.

The Lift Association Data Mining Classification in BBP-LA framework uses an additional lift to support and confidence in order to increase the accuracy of the diseased patterns being generated. Let us consider two diseased Patterns $A_i \rightarrow B_i$, then the support value is obtained as given below

$$S(A_i \cup B_i) = {}^{I_i}/_{I_n} \tag{6}$$

From (6), the support is the ratio of the number of input patterns obtained through A_i and B_i to the total number of diseased patterns in the dataset. The confidence value is based on the ratio of how frequent B_i(i.e, stroke) occurs among all A_i(i.e., heart) and is given as below

$$Confidence = {}^{S(A_i \cup B_i)}/_{S(A_i)} \tag{7}$$

The lift value for Association Data Mining Classification in BBP-LA framework is the ratio of the confidence value to the support of B and is given as

$$Lift = {}^{Confidence}/_{S(B_i)} \tag{8}$$

The measure of lift in BBP-LA framework obtains the deviation of the rule from A_i and B_i which lies between 0 and 1. If the value of lift is greater than 1, it indicates that both stroke and heart disease occur more often, a value less than 1 indicates that stroke and heart disease occurs less often whereas a value closer to 1 indicates that stroke and heart disease occur often. This finally helps in improving the accuracy of the diseased patterns identified.

Experimental Setup

In this section, the Binary Back Propagation based Lift Association framework is evaluated from different points of view using various patterns (i.e., heart disease and stroke). The framework BBP-LA is implemented in JAVA and the data used for measuring the efficacy of the proposed framework, is Cleveland Clinic Foundation

Heart disease data set available at http://archive.ics.uci.edu/ml/datasets/Heart+Disease. The dataset used in BBP-LA include 76 raw attributes where only 5 attributes are used for conducting the experiments. The data set contains 303 rows of which 297 are complete. Six rows contain missing values and they are removed from the experiment.

The BBP-LA framework uses 35 samples to conduct the experiments. The experimental work is compared against the existing Stroke and Ventricular Arrhythmias (SVA) [1] and spiking neural networks on stroke (SNN-S) [2] to identify the effectiveness of BBP-LA. The performance of the BBP-LA framework is measured in terms of precision, accuracy, heart disease and stroke identification rate with minimum processing time.

Discussion

To evaluate the framework of BBP-LA, for early detection of heart disease and stroke pattern, two well-known methods are compared, which are Stroke and Ventricular Arrhythmias (SVA) [1] and spiking neural networks on stroke (SNN-S) [2].

Impact of accuracy

Accuracy using BBP-LA framework refers to the measure of closeness of diseased value to the actual value. It is the ratio of sum of disease people correctly diagnosed as diseased and healthy people correctly diagnosed as healthy to the total number of samples carried out for experiment. It is measured in terms of percentage (%).

$$A = \frac{(Disease\ people\ diagnose\ diseased) + (Healthy\ people\ diagnose\ healthy\ )}{Total\ number\ of\ samples} * 100 \quad (9)$$

A (using BBP-LA) = (2+2)/5 * 100 = 80
A (using SVA) = (2+1)/5 * 100 = 60
A (using SNN-S) = (1+1)/5 * 100 = 40

Table 1 shows the accuracy of the disease patterns generated to the healthy person of BBP-LA framework with two disease classification methods over Cleveland Clinic Foundation Heart disease data set.

Table 1: Tabulation for accuracy

No. of samples	Accuracy (%)		
	BBP-LA	**SVA**	**SNN-S**
5	80.25	60.33	41.15
10	74.35	45.35	38.33
15	70.22	40.14	35.15
20	68.45	38.55	32.15
25	71.35	44.85	43.25
30	76.55	52.35	48.55
35	80.35	55.18	52.65

Figure 3 given below shows the accuracy rate for BBP-LA framework, SVA [1] and SNN-S [2] versus thirty five different samples. The accuracy rate returned over BBP-LA framework increases gradually though not linear for differing number of samples because of the dynamic changes observed with different pattern sets.

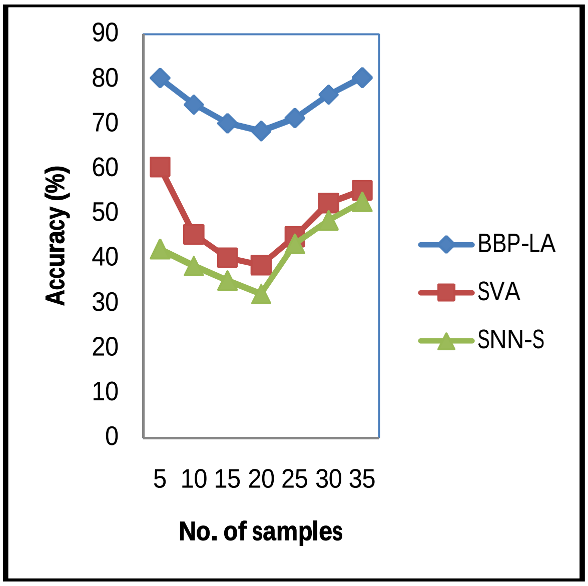

Figure 3: Measure of accuracy

From figure 3, it is illustrative that the accuracy rate is improved using the proposed framework BBP-LA. For example with 5 samples, the accuracy rate was 80.25 percent using BBP-LA whereas SVA recorded 60.33 percent and 42.15 percent in SNN-S. By observing the dense samples, the accuracy rate is improved. This is because with the application of List Association Data Mining Classification, the accuracy rate is increased.

With the help of the lift value, in addition to the confidence and support value, efficiently validates the association rule and improves the accuracy by 24 – 43 % compared to SVA. In addition, by measuring the lift value, that obtains the ratio of support value to the confidence improves the accuracy of the diseased patterns identified at an early stage by 34 – 53 % compared to SNN-S.

Impact of precision

Precision also known as positive predictive value refers to the amount of disease people diagnosed as disease to the sum of the disease person diagnose as diseased and healthy person identified as healthy. It is measured in terms of percentage (%).

$$P = \frac{\text{Disease people diagnose as diseased}}{(\text{Disease people diagnose diseased}) + (\text{Healthy people diagnose healthy})} * 100 \qquad (10)$$

P (using BBP-LA) = (2)/ (2 + 2) * 100 = 50
P (using SVA) = (1)/ (1 + 2) * 100 = 33.33
P (using SNN-S) = (1)/(1 + 3) * 100 = 25

Table 2 shows the number of samples selected from Heart disease data set using three disease classification methods and their precision rates. The results shows that the framework BBP-LA produce the largest precision rate, which means that it identifies the most relevant stroke and heart disease at an early stage.

Table 2 Tabulation for precision

No. of samples	**Precision (%)**		
	BBP-LA	**SVA**	**SNN-S**
5	50.23	34.25	25.15
10	62.5	52.33	48.28
15	68.43	65.21	53.25
20	71.35	68.34	60.14
25	74.28	70.28	62.13
30	78.33	73.24	67.19
35	81.45	75.11	70.23

Figure 4 shows the result of precision rate versus the varying number of samples. In order to investigate the precision rate and better perceive the efficacy of the proposed BBP-LA framework, substantial experimental results are illustrated in Figure 4 and compared against the existing SVA [1] and SNN-S [2] respectively for different implementation runs. Higher, the number of samples, more successful the framework is. The results reported here confirm that with the increase in the number of samples, the precision rate also increases. The process is repeated for 35 samples for conducting experiments.

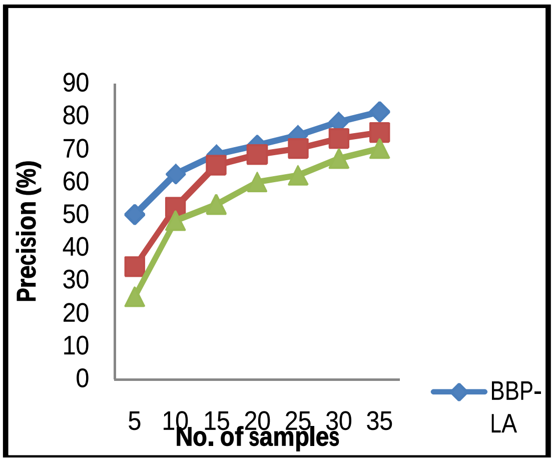

Figure 4: Measure of precision

As illustrated in Figure 4, the proposed BBP-LA framework performs relatively well when compared to two other methods SVA [1] and SNN-S [2]. The precision rate using BBO-LA framework is improved with the application of binary back propagation neural network where the extraction of disease patterns is performed twice increasing the precision score on heart disease and stroke identification process by 4 – 31 % compared to SVA [1]. In addition, the binary value applied in Back Propagation Neural Network to identify the disease patterns performs two time classification of input nodes, into one of two possible cases as either '0' or '1', produce higher precision score on the heart and stroke disease identification by 14 – 39 % compared to SNN-S.

Impact Of Processing Time

The processing time using the BBP-LA framework is the difference between the time taken to identify the disease and hidden patterns to the hidden patterns.

$$Time = Time\ (\frac{(DP_i) - (HP_i)}{HP_i}) \tag{11}$$

Time (using BBP-LA) = (2*10) – (2*7)/ (2*7) = 0.42
Time (using SVA) = (3*10) – (3*6)/ (3*6) = 0.66
Time (using SNN-S) = (4*10) – (4*5)/ (4*5) = 1.0

Table 3 shows the number of disease patterns selected from Heart disease data set using three disease classification methods and their processing time with respect to disease patterns and hidden patterns. Seventy disease patterns are considered for the purpose of experimentation.

Table 3: Tabulation for processing time

No. of disease patterns	Processing time (ms)		
	BBP-LA	**SVA**	**SNN-S**
10	0.42	0.66	0.8
20	0.59	0.73	1.05
30	0.68	0.70	1.12
40	0.82	0.85	1.20
50	0.85	0.88	1.25
60	0.89	0.91	1.31
70	0.92	0.93	1.35

In order to reduce the processing time with the static and dynamic changes based disease patterns, the time taken to identify the disease and hidden patterns for effective handling of both static and dynamic changes is considered. In the experimental setup, the number of disease patterns ranges from 10 to 70 is illustrated in figure 5. The processing time using the framework BBP-LA provides comparable values than the state-of-the-art methods.

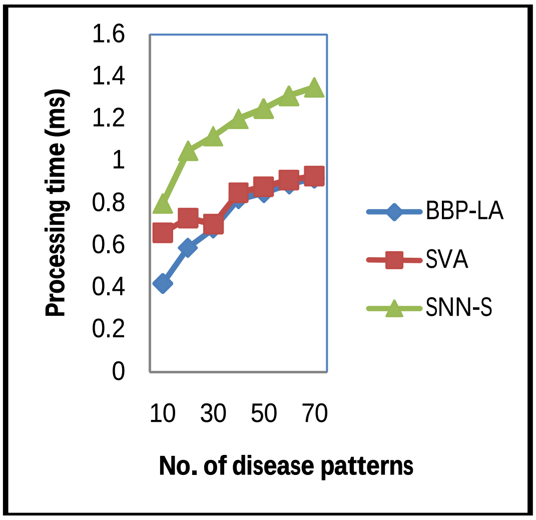

Figure 5: Measure of processing time

The targeting results of processing to identify the heart and stroke disease at an early stage using the BBP-LA framework is compared with two state-of-the-art methods SVA and SNN-S in figure 5 is presented for visual comparison based on the number of disease patterns. Our framework BBP-LA differs from the SVA [1] and SNN-S [2] in that we have incorporated Neural Network Pruning algorithm that employ activation of hidden unit for pattern identification of stroke and heart disease in health care industry.

With the objective of minimizing the processing time in BBP-LA framework, different result set for disease patterns is measured based on the synaptic weights of neural network to obtain the desired output for a set of input patterns. This activation of hidden unit applied in BBP-LA framework reduces the time taken for pattern identification of disease by 2 – 23 % compared to SVA. Furthermore, with the effective application of least square function in Neural Network Pruning algorithm, the error rate is reduced reducing the processing time to identify the patterns in BBP-LA by 46 – 90 % compared to SNN-S.

Impact of Heart Disease And Stroke Identification Rate

The influence of heart disease and stroke identification rate respect to the seventy disease patterns and thirty five samples is listed in table 4 and comparison is made with two other existing schemes.

Table 4 Tabulation for heart disease and stroke identification rate

Methods	Impact of heart disease and stroke identification rate (%)
BBP-LA	75.33
SVA	69.42
SNN-S	65.22

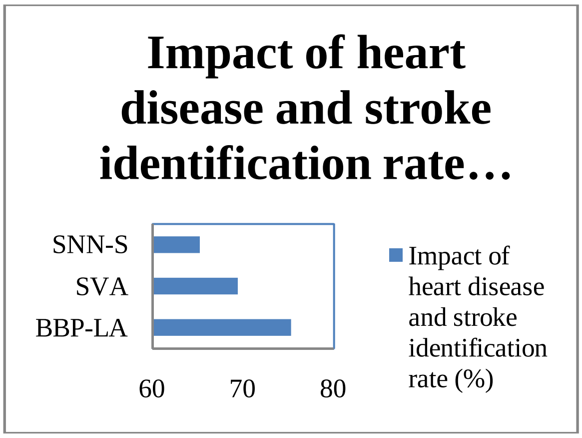

Figure 6: Measure of impact of heart disease and stroke identification rate

Figure 6 shows the measure of heart disease and stroke identification rate using the proposed BBP-LA framework and comparison made with two other methods, SVA and SNN-S respectively using values from table 4. From the figure we can note that the heart disease and stroke identification rate is increased in the proposed BBP-LA framework when compared to two other existing methods. This is because of the application of Neural Network Pruning (NNP) algorithm with binary back propagation that and further reducing the error rate. As a result, increases the efficiency of pattern identification improving robustness in terms of heart disease and stroke identification rate using BBP-LRA framework by 7.84 % compared to SVA and 6.05 % compared to SNN-S respectively.

Conclusion

Identifying hidden patterns and obtaining relationship with disease patterns have motivated us to propose an integrated solution for improving the accuracy and precision rate of identifying disease patterns at an early stage by significantly minimizing the processing time. To achieve this goal, Binary Back Propagation based Lift Association (BBP-LA) framework for improving the heart disease and identifying the stroke rate is presented. Disease extraction using binary with the aid of Binary Back Propagation Neural Network significantly improve the precision score on heart disease and stroke identification process. We also analyzed the activation of hidden unit for pattern identification that reduces the processing time taken for effective identification of heart and stroke disease that further improves the efficiency of pattern identification in a significant manner. To implement our framework, we devised a Neural Network Pruning algorithm that included the least square function using synaptic weights and accompanied error to reduce the processing time for effective identification of patterns. Experiments conducted on Cleveland Clinic Foundation Heart disease data set prove the efficiency of our framework that increases the robustness in terms of heart disease and stroke identification rate. The BBP-LA framework attains the performance improvements over other classification and prediction models with the experiments conducted with various conditions using JAVA in terms of precision, accuracy rate and processing time.

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